Student Enrollment Patterns and Achievement in Ohio's Online Charter Schools

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We utilize state data of nearly 1.7 million students in Ohio to study a specific sector of online education: K–12 schools that deliver most, if not all, education online, lack a brick-and-mortar presence, and enroll students full-time. First, we explore e-school enrollment patterns and how these patterns vary by student subgroups and geography. Second, we evaluate the impact of e-schools on students' learning, comparing student outcomes in e-schools to outcomes in two other schooling types, traditional charter schools and traditional public schools. Our results show that students and families appear to self-segregate in stark ways where low-income, lower achieving White students are more likely to choose e-schools while low-income, lower achieving minority students are more likely to opt into the traditional charter school sector. Our results also show that students in e-schools are performing worse on standardized assessments than their peers in traditional charter and traditional public schools. We close with policy recommendations and areas for future research.

Keywords: achievement; computers and learning; econometric analysis; educational policy; regression analyses; technology

Online education is fast rising as a potential strategy to diversify education choices at all levels of education. In this article, we focus on a specific sector of online education: K–12 schools that deliver most, if not all, education online, lack a brick-and-mortar presence, and enroll students full-time. In Ohio (as well as other places) and for the purposes of this article, these schools will be referred to as e-schools. Advocates of e-schools argue that new technologies that make online learning possible have the potential to expand the depth and breadth of courses available to students, provide options for new locations and schedules for learning, and perhaps introduce effective new ways to deliver education in a variety of settings (Finn & Fairchild, 2012). Questions have also been raised about potentially negative outcomes that can arise when e-schools are introduced into K–12 public education such as increased pressure among stakeholders to compete for limited resources, profiteering by private companies, and ineffective learning outcomes for K–12 and postsecondary students (Center for Research on Education Outcomes [CREDO], 2015; Chingos & Schwerdt, 2014; Hart, Friedmann, & Hill, in press; Heissel, 2016; Molnar, 2013).

The limited body of research paints a neutral to negative picture where students attending e-schools often fair worse than their peers in traditional learning settings (CREDO, 2015).[1] We add to this literature in two ways using the case of Ohio, which has authorized e-schools since the early 2000s. First, we explore e-school enrollment patterns and how these patterns vary by student subgroups and geography. Second, we evaluate the impact of e-schools on students' learning comparing student outcomes in e-schools to outcomes in two other schooling types, traditional charter schools and traditional public schools.[2] Specifically, we ask the following research questions:

Research Question 1: Which students are opting into Ohio's e-schools, and what are their characteristics in comparison with their peers in traditional school settings?

Research Question 2: How does the achievement for students in e-schools compare to students in face-to-face traditional public schools and charter schools?

Our findings indicate that (a) enrollment in Ohio e-schools is steadily increasing and growth and student participation rates

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Educational Researcher, Vol. 46 No. 1, pp. 44–57
DOI: 10.3102/0013189X17692999

vary remarkably by student demographics and (b) performance of students in e-schools is considerably lower than peers in traditional charter schools and traditional public schools. The results of this study have important implications for the design of future school choice policies that incorporate online forms of schooling, in addition to informing future studies that seek to examine the effectiveness of online schooling in K–12 settings.

Background and Relevant Literature

Online schools introduce new political and governance challenges to K–12 public education. These school forms theoretically break the barriers associated with physical school choice policies and allow for widespread enrollment across geographic boundaries (Huerta, Gonzalez, & d'Entremont, 2006). When this technological feature is introduced into an existing policy and institutional system where students are expected to enroll in their local schools, new challenges emerge as districts lose students and the associated funding to online schools. In this study, we explore how introducing online schooling in the state of Ohio has implications for issues of school choice, segregation of students by school type and demographics, and student achievement.

E-Schools in Ohio: A Confluence of School Choice and Technology

In Ohio, traditional charter schools are referred to as *community schools*, and online charter schools are termed *e-schools*. A variety of providers can operate e-schools, including school districts, nonprofits, and private for-profit companies. Students typically opt out of their local school district and enroll in an e-school and have a fully online learning experience.

There is a lack of information and/or understanding about the pedagogical environment of e-schools. However, case studies suggest that students often experience content via multimedia (e.g., online videos, presentations, reading, and other curricular materials), have assignments and homework similar to students in traditional school environments, and interact with teachers via email, chat, or other online channels (Ahn, 2011). Students in fully online e-schools often work from home, with materials and computer resources mailed to their residence. However, some blended models of e-schools may allow students to attend a physical school building for some activities. Recent studies also suggest that independent, self-paced instruction is the norm in e-schools and that student-teacher interaction may be limited (Gill et al., 2015).

Heterogeneity in School Choice Decisions

There are a number of potential motivations for providing students and parents the ability to choose a school other than their traditional public school. The arguments generally range from increasing efficiency in the production of education through enhanced competition, maximizing social efficiency by matching students' and parents' demands with the supply of schools, or increasing innovation by reducing bureaucratic barriers (Chubb & Moe, 1990; Levin, 2009). However, these ideas are predicated on the assumption that parents will make educational choices that align with the original intent of the policy.

However, research shows that school choice decisions vary for students from different backgrounds and achievement levels. Reasons for this include information asymmetry, family budget constraints, and variation in family values. For example, Cullen, Jacob, and Levitt (2006) found that when students in low-performing schools were provided the opportunity to transfer to a new and better performing school, White and higher achieving students and students from more affluent families were more likely to utilize the open enrollment policy than their non-White, poorer, and lower achieving peers. If information is costly to acquire (e.g., financially, intellectually, linguistically), low-income families often base decisions on easy to access information (Hastings & Weinstein, 2008). Researchers have found that students from at-risk backgrounds placed considerably less weight on academic indicators when making a decision (Bauch, & Goldring, 1995; Goldring & Shapira, 1993; Hastings, Kane, & Staiger, 2009). Furthermore, Welsh, Duque, and McEachin (2016) found that conditional on leaving the same school, low performing students were considerably more likely to attend a school with low average achievement than their higher achieving peers. Given the dynamics around school choice, an important and open issue pertaining to e-schools is to understand how students and families choose which school to attend.

Impact of E-Schools on Student Outcomes

Compared to the parallel literature on the effect of various forms of school choice (e.g., traditional charter schools, vouchers, private schools), there is relatively little research on how online learning works for K–12 students (Barbour & Reeves, 2009). Online learning for K–12 students occurs in a variety of settings such as: students taking an online course or two to supplement offerings at their traditional public school, learners using online courses for credit recovery, students using online tools to complement face-to-face courses, and students fully enrolling in e-schools. In this section, we review the relevant literature on the impact of online learning on student outcomes.

A national evaluation of online charter schools provides the best evidence to date about the impact of online schools on student learning (CREDO, 2015). The study found that students in online charter schools perform significantly worse than students with similar demographics and prior achievement in traditional public schools, often ranging from –.10 *SD* to –.30 *SD*. The study also provides detailed information on the programmatic and curricular differences between online and traditional public schools. However, the authors do not examine e-school enrollment patterns across subgroups of students, nor do they examine the heterogeneity of performance in e-schools by students' prior achievement. Recent studies of online course taking and online learning in higher education also suggest that students in online settings learn less than students in traditional settings (Hart et al., in press; Heissel, 2016). Furthermore, students in home-based and online charter schools in California in the early 2000s performed worse than their peers in traditional public schools (Buddin & Zimmer, 2005; Gill, Timpane, Ross, Brewer, & Booker, 2007).

As policymakers and other stakeholders are confronted with a dizzying array of schooling types, there is increasing need for a better understanding of the potential consequences of policy decisions, such as allowing different types of online learning (e.g., statewide virtual schools, cyber charter schools, standalone online courses), whether to allow both public and private providers, and ensuring that students and families have quality learning experiences in online settings (Ahn, 2011; Huerta et al., 2006). There is also a need to understand how introducing online schooling influences student choices to enroll in online options and shapes the experiences they may have in their public education system. The results of this article attempt to address these concerns and add to the small but growing literature on the impact of e-schools on student enrollment patterns and achievement.

Data Sources

The analyses in this study utilize student-level data for all Ohio students in a traditional public school, charter school, and e-school in kindergarten through 12th grade. Our data cover the 2009–2010 to 2012–2013 school years and was provided by the Ohio Department of Education. There are approximately 1.7 million students per year.[3] The data include student performance on the Ohio Achievement Assessments (OAA) and the high school Ohio Graduation Test (OGT) in math, reading, science, and history. Students complete the OAA in Grades 3 through 8 and the OGT in Grade 10.[4] We standardize students' OAA and OGT performance by grade, year, and subject. The data include standard demographic information for students, including race and ethnic membership, free and reduced price lunch (FRPL) status, participation in special programs (e.g., gifted education, special education, English as a second language), grade level, attendance and suspension data, and students' district of residence and district of attendance. We also supplement the data with district geographic indicators from the NCES Common Core Data.

Methods

We use a linear probability model (LPM) to evaluate student enrollment differences between two main public school choice options: e-schools and charter schools.[5,6] Specifically, we estimate the following LPM to examine observable differences between students who enroll in an e-school versus a charter school:

$$D_{isdt} = \lambda Y_{isd(t-p)} + \beta X_{isdt} + \alpha_t + \alpha_{d(t-p)} + \varepsilon_{isdt}\,, \tag{1}$$

where the enrollment of a student i, in school s, in district d, and time t in a e-school ($D_{igst} = 1$) versus a charter school ($D_{igst} = 0$) as a linear function of his or her prior standardized math OAA achievement, $Y_{isd(t-p)}$; a vector of student characteristics, X_{isdt}, including indicators for racial ethnic membership with White students as the reference group, FRPL participation, special education participation, English language learner status, whether he or she repeated a grade, and whether he or she participated in gifted education as measured in a baseline year. For elementary and middle school students, we define the baseline year as the prior school year, and for high school students, we define the baseline year as eighth grade. We also include time α_t and district of residence fixed effects ($\alpha_{d(t-p)}$) and an idiosyncratic student-level error term (ε_{isdt}). The inclusion of $\alpha_{d(t-p)}$ restricts the comparison of enrollment patterns to students who live within the same geographic region. The coefficient vector of interest β captures whether specific groups of students are more or less likely to enroll in an e-school rather than a charter school. We also test for geographic heterogeneity by interacting suburban, rural, and urban indicators with X_{isdt}, with town as the reference group. We use school-level cluster robust standard errors to account for within-school correlation and heterogeneity in the student-level residuals.

We are also interested in evaluating the achievement differences between students in choice schools (charter and e-schools) versus traditional public schools. We estimate a standard value-added model to evaluate the differences in achievement among the three types of schools in our study[7]:

$$\begin{aligned} Y_{isdt} = \lambda Y_{isd(t-p)} + \delta_1 charter_{isdt} + \delta_2 e-school_{isdt} + \\ \beta X_{isdt} + \alpha_t + \alpha_{s(t-p)} + \varepsilon_{isdt}\,, \end{aligned} \tag{2}$$

where the current achievement for student i in school s district d and year t, Y_{isdt}, is a function of his or her prior achievement, $Y_{isd(t-p)}$; binary indicators $charter_{isdt}$ and, $e-school_{isdt}$, which take a 1 if a student attends a charter school or e-school, respectively, in the current year, and a 0 if a student attends a traditional public school; and the same student-level control variables, X_{isdt}, and time fixed effects, α_t, as Model 1. For elementary and middle school students, we use as their current achievement standardized math and reading achievement on OAA, and for high school students, we use as their current achievement 10th-grade standardized achievement on one of five Ohio Graduation Tests (math, reading, science, social studies, and writing). Given high school graduation is conditional on passing the OGTs, we also estimate models exploring whether students in e-schools are more or less likely to pass the OGTs than their peers in charter or traditional public schools using binary dependent variables in an LPM framework. In these models, we include separate binary dependent variables for whether students passed one of the five subjects as well as whether students passed all five of the subjects. Prior achievement is defined the same as Model 1.

In Model 2, we also condition on students' prior school fixed-effects $\alpha_{s(t-p)}$, which restricts our comparison of achievement differences between charter and e-school students and their peers in traditional public schools to students who attended the same school in the prior year. Variations of Model 2 have been used to evaluate the effect of teachers, schools, and education policies and practices on students' achievement and other outcomes (Aaronson, Barrow, & Sander, 2007; Angrist, Hull, Pathak, & Walters, 2016; Deming, 2014; Guarino, Reckase, & Wooldridge, 2015; Hanushek, Kain, Rivkin, & Branch, 2007; Kane, McCaffrey, Miller, & Staiger, 2013; Kane & Staiger, 2008; McEachin, Welsh, & Brewer, 2016). We also extend Model 2 to examine how e-school and charter school achievement varies by students' prior achievement.[8] We use school-level cluster robust standard errors to account for within-school correlation and heterogeneity in the student-level residuals.

Results

Before diving into the regression results, we present enrollment trends across the three types of public schools in Ohio as well as descriptive statistics on the students who attend these schools.

Enrollment Trends

In Table 1, we present enrollment trends by grade level and school type. E-school enrollments rose steadily from approximately 22,000 students in 2010 to over 35,000 students in 2013, an increase of approximately 60% over a four-year period. High schools make up the majority of e-school enrollment. In comparison, enrollment in charter schools increased by approximately 4,000 students (6%), and enrollment in traditional public schools decreased by approximately 71,000 students (5%) during this time period. Although e-school enrollments account for only 2% of Ohio's student population in 2013, they experienced the largest growth in this four-year period.

We also show the geographic spread of charter school (light circles) and e-school (gray shading) enrollments in Figure 1. We use circles to represent charter schools across the state. We use gray shading and school district boundaries to show how e-school enrollment varies across the state. The darker gray shading indicates that more students within a given district are enrolled in e-schools. That vast majority of charter schools serve Ohio's urban cities. E-school enrollment also overlaps with charter school enrollment in these cities. In an analysis described in more detail in the following, we use this overlap to evaluate which students in a given school district prefer charter schools to e-schools.

Student Characteristics in E-Schools

Although many students appear to have access to both charter schools and e-schools, we find interesting differences in students' characteristics among the school types. In Table 2, we present the average demographics across the traditional public schools and charter schools and e-schools, separated by grade span. Students in e-schools and charter schools have lower baseline achievement than their peers in traditional public schools, are more likely to qualify for the federal free and reduced price lunch program, and are less likely to participate in gifted education. However, we see interesting differences along racial and ethnic lines between e-school and charter schools. Approximately 50% to 60% of charter school students are Black, compared to approximately 10% in e-schools and 12% in traditional public schools. However, it is important to keep in mind that charter schools are clustered in urban areas, which have much larger percentages of Black students than the state as a whole.

We next take a more refined look at the demographic differences among students in traditional public schools, charter schools, and e-schools. In the first two columns of Table 3, we present the student demographics weighted by the number of charter school students within a district's border. This will upweight students' demographics in districts with larger shares of charter schools, downweight students in districts with smaller shares of charter schools, and remove students in districts without charter schools. In these columns, we see that traditional public school students' prior achievement and FRPL status fall closer to the charter school demographics described in Table 2. Interestingly, we see that elementary students in traditional public schools are much less likely to be Black than students in charter schools, but high school students in traditional public schools are more likely to be Black than high school students in charter schools.

We conduct a similar analysis in Columns 3 and 4, but this time weight traditional public school demographics by the number of e-school students within the district's boundary. Again, we see students' prior achievement and FRPL status in traditional public schools in districts with larger shares of e-school enrollment look more similar to the average characteristics of e-school students. However, we still see important racial and ethnic differences, especially in high school. Only 45% of traditional public school students in Column 4 are White, whereas more than 80% of e-school high school students are White.

Finally, we take a closer look at e-school demographics for kids who live in residential districts with charter schools within their boundaries. Specifically, we link both e-school and charter school students to their residential district (their assigned district based on their home address). We then weight e-school demographics by the number of charter school students within their residential district, providing a more direct comparison between e-school and charter school student demographics. In Columns 5 and 6, we see that the e-school students have approximately similar prior achievement and FRPL status to charter schools, although elementary e-school students are slightly less likely to qualify for the FRPL program. Interestingly, we still find stark racial and ethnic differences among e-school students who live near charter schools and their charter school peers. For example, 80% and 60% of elementary and high school students are White in e-schools, compared to just 25% and 37% in charter schools. It is important to keep in mind these are just descriptive patterns. We use a regression framework to more carefully look at the demographic differences between e-school and charter school students.

Regression Analysis

The results of the Model 1 are presented in Table 4. Interestingly, even conditional on students' prior achievement, poverty status, and residential district of record, Black students are 29% and 24% points less likely to attend an e-school compared to White students in elementary/middle schools and high schools, respectively. Similarly, Hispanic students are 13 and 9 percentage points less likely to attend an e-school than White students in elementary/middle schools and high schools, respectively. We see similar patterns for special education students as well, although on a smaller magnitude.

In Columns 2 and 3 for elementary/middle school students and Columns 5 and 6 for high school students, we test whether the difference in e-school enrollment between Hispanic and

Table 1
Annual K–12 Enrollment by School Sector in Ohio

	2010			2011			2012			2013		
Grade	Traditional Public School	E-School	Charter School	Traditional Public School	E-School	Charter School	Traditional Public School	E-School	Charter School	Traditional Public School	E-School	Charter School
K	118,240	788	6,503	115,772	910	6,562	117,846	1,074	8,041	115,747	1,272	8,802
1	120,699	800	6,194	120,036	903	6,311	119,195	986	6,929	117,242	1,132	7,705
2	120,286	861	5,426	119,273	925	5,600	119,244	1,070	6,380	115,197	1,202	6,867
3	122,983	917	5,310	119,618	965	5,361	119,297	1,111	6,055	116,259	1,189	6,272
4	123,678	1,014	4,893	122,491	1,150	5,022	120,562	1,192	5,610	116,600	1,338	5,857
5	123,407	1,057	4,463	123,496	1,298	4,963	123,168	1,461	5,381	117,977	1,500	5,538
6	123,859	1,250	4,378	122,806	1,433	4,609	123,929	1,755	5,228	120,186	1,921	5,628
7	122,764	1,532	3,767	122,532	1,773	4,024	123,357	2,096	4,436	120,118	2,417	4,953
8	122,219	1,799	3,331	120,439	1,987	3,741	121,816	2,538	4,061	119,908	2,875	4,190
9	134,873	4,248	4,951	130,395	4,359	4,684	128,880	5,351	5,163	126,126	5,518	2,476
10	124,661	2,692	3,528	122,005	3,451	3,645	119,698	4,152	3,781	116,293	4,690	1,865
11	109,278	2,921	3,202	105,218	3,610	3,517	103,177	4,991	4,056	98,805	5,730	1,445
12	102,202	2,294	3,103	101,563	3,146	3,506	101,469	4,073	4,053	97,620	4,728	1,570
Total	1,569,149	22,173	59,049	1,545,644	25,910	61,545	1,541,638	31,850	69,174	1,498,078	35,512	63,168

Black students, compared to White students, varies by districts' geographic location. Specifically, in separate models, we interact these two race indicators with three geographic indicators: city (or urban), suburban, and rural, with town as the reference group. We cannot include the main effect of the geographic indicators as they are absorbed by the district of residence fixed effects. The results in Column 2 show that the difference between Black and White students' enrollment in e-school (vs. charter school) is primarily driven by differences in city and suburban districts for elementary school students. We do not find statistically significant interactions for Black high school students. Hispanic elementary students in city and suburban districts (Column 3) are less likely to enroll in an e-school, while only Hispanic high school students in a rural district are significantly less likely than their White peers to enroll in an e-school. However, it is important to keep in mind that the population of Hispanic students in Ohio is much smaller than that of White or Black students, and these interactions need to be interpreted with caution.

We flesh out these race-by-geography differences more clearly in Table 5. Each point estimate from Table 5 refers to the percentage point difference in the likelihood for a Black or Hispanic student to enroll in an e-school compared to a White student, separately for town, city, suburban, and rural districts.[9] The results in Panel A show stark differences in the marginal probability of Black versus White students enrolling in online elementary/middle and high schools. For elementary and middle schools, Black students in city, suburban, and rural districts are 17 to 30 percentage points less likely than White students to enroll in e-schools, and for high schools, Black students in city and suburban districts are 25 percentage points less likely to enroll in e-schools than White students. The results in Panel B show similar patterns for Hispanic students but at a smaller magnitude.[10]

We present the achievement differences for students in e-schools and charter schools relative to students in traditional public schools in Table 6. Across all subjects and grade spans, we see that students in e-schools score significantly lower than students in traditional charter and public schools, even conditional on a variety of control variables. Elementary and middle school students in e-schools score .37 *SD* and .19 *SD* worse in math and reading, respectively, than students in traditional public schools and approximately .4 *SD* and .22 *SD* worse than charter school students. We see similar patterns for high school students across the 10th-grade OGT assessments in math, reading, science, social studies, and writing (see Panel B). These results mirror the national findings from CREDO (2015), which found students in e-schools across the United States, including Ohio, scored significantly worse on math and reading assessments than similar students in traditional public schools. Traditional charter high school students have mixed results ranging from significantly better in science, equal in math, and significantly worse in reading, social studies, and writing. Furthermore, in all subjects, e-school students perform worse than charter school students.

In Table 7, we report the results from an LPM predicting the likelihood of passing each of the high school OGTs as well as passing all of them. Similar to Panel A, e-school students are significantly less likely to pass the OGTs than students in traditional public schools, ranging from 3 percentage points less in reading to 14 percentage points if you include all of them at once (all subjects). Furthermore, e-school students are significantly less likely to pass than their peers in charter schools.

In Tables 8 and 9, we evaluate how the achievement trends in Tables 6 and Table 7 vary by students' prior achievement, as measured by tertiles of students' prior achievement included in Model 2. Specifically, we report the marginal effects of the interactions between tertiles of students' prior achievement

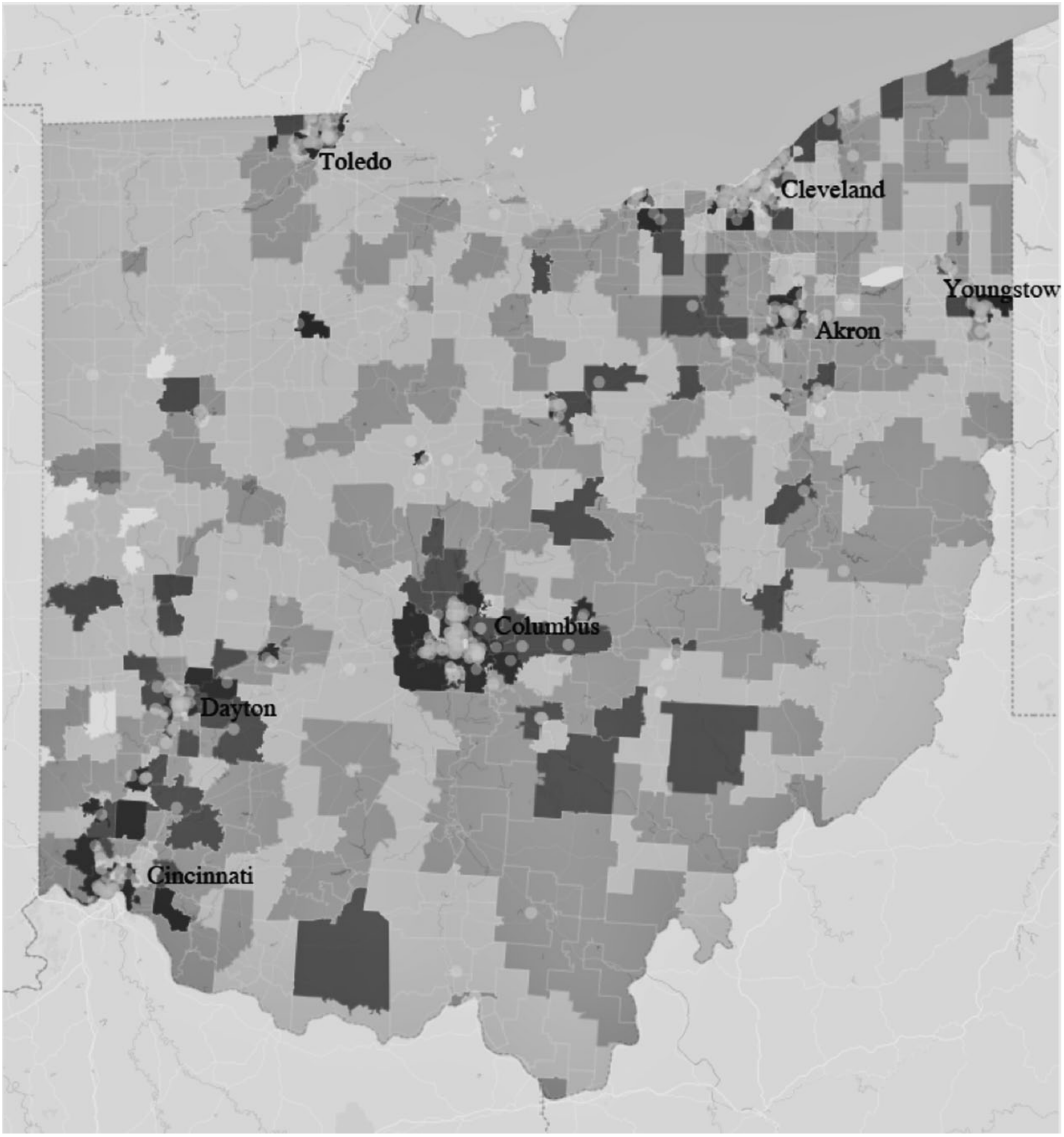

FIGURE 1. *2010 charter and e-school enrollments in Ohio*
Source. Authors' calculations from Ohio Department of Education's student-level data.

and indicators for attending an e-school or charter school. The coefficients can be interpreted as the achievement of e-school or charter school students relative to students with the same prior achievement level in a traditional public school. The results for elementary/middle school students in Table 8 show that regardless of e-school students' prior achievement levels, all e-school students perform worse than their peers with similar prior achievement. However, the negative effects are less pronounced for students at the higher end of the achievement levels. For example, e-school students in the top third of the prior reading distribution experience negative effects of –.1 *SD* while students from the bottom third of the prior distribution experienced negative effects of –.26 *SD*. We see similar patterns for high school students. Interestingly, with the exception of writing, charter school students from the top third of the eighth-grade OAA distribution are performing on par with their traditional public school peers.

In Table 9, we further examine these patterns by evaluating the heterogeneity in OGT passage rates by students' prior achievement. Contrary to the achievement analysis, e-school students from the top third of the distribution are passing the 10th-grade OGTs at the same rate as students in traditional public schools. Even though students in the top third of the distribution are passing at a similar rate, it is important to keep in mind

Table 2
Ohio Student Demographics Across School Types

	Traditional Public School Students				E-School Students				Charter School Students			
	Elementary and Middle School (*N* = 1,312,219)		High School (*N* = 161,188)		Elementary and Middle School (*N* = 14,523)		High School (*N* = 1,691)		Elementary and Middle School (*N* = 47,216)		High School (*N* = 1,312)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
High school achievement												
10th-grade math OGT (*z* score)			0.085	1.020			–0.575	0.921			–0.678	0.948
10th-grade reading OGT (*z* score)			0.040	0.977			–0.373	1.010			–0.579	1.050
10th-grade science OGT (*z* score)			0.089	0.833			–0.431	0.802			–0.492	0.848
10th-grade writing OGT (*z* score)			–0.018	0.971			–0.610	0.930			–0.677	0.991
10th-grade social studies OGT (*z* score)			0.071	0.847			–0.503	0.873			–0.498	0.854
Pass 10th-grade math OGT			0.894	0.308			0.742	0.438			0.694	0.461
Pass 10th-grade reading OGT			0.914	0.281			0.839	0.368			0.784	0.411
Pass 10th-grade science OGT			0.836	0.370			0.644	0.479			0.601	0.490
Pass 10th grade social studies OGT			0.908	0.289			0.796	0.403			0.768	0.423
Pass 10th-grade writing OGT			0.875	0.330			0.679	0.467			0.682	0.466
Pass all five 10th-grade OGTs			0.765	0.424			0.514	0.500			0.482	0.500
Baseline math OAA (*z* score)[a]			0.177	0.826			–0.197	0.742			–0.478	0.727
Baseline reading OAA (*z* score)[a]			0.167	0.770			–0.072	0.731			–0.327	0.737
Elementary and middle school achievement												
Math OAA (*z* score)	0.083	0.939			–0.517	0.896			–0.515	0.842		
Reading OAA (*z* score)	0.073	0.908			–0.241	0.958			–0.439	0.901		
Prior math OAA (*z* score)[b]	0.083	0.934			–0.388	0.905			–0.511	0.857		
Prior reading OAA (*z* score)[b]	0.080	0.882			–0.152	0.914			–0.406	0.871		
Student demographics												
English language learner	0.014	0.117	0.013	0.113	0.001	0.0275	0.006	0.077	0.029	0.167	0.026	0.159
Gifted education	0.248	0.432	0.270	0.444	0.029	0.168	0.150	0.357	0.012	0.11	0.063	0.242
Free and reduced price lunch program	0.428	0.495	0.351	0.477	0.600	0.49	0.591	0.492	0.814	0.389	0.745	0.436
Special education	0.132	0.338	0.117	0.321	0.158	0.365	0.154	0.361	0.181	0.385	0.242	0.429
Male	0.509	0.5	0.501	0.500	0.502	0.5	0.347	0.476	0.493	0.5	0.504	0.500
Number of disciplinary actions	0.252	1.12	0.224	0.979	0.005	0.089	0.455	1.490	0.388	1.080	0.521	1.410
Repeated grade	0.003	0.055	0.002	0.049	0.017	0.13	0.005	0.069	0.015	0.122	0.005	0.068
Black student	0.125	0.331	0.113	0.317	0.106	0.308	0.076	0.266	0.623	0.485	0.485	0.500
Hispanic student	0.033	0.178	0.029	0.168	0.028	0.165	0.037	0.189	0.071	0.257	0.075	0.263
White student	0.783	0.412	0.807	0.395	0.821	0.384	0.846	0.361	0.246	0.431	0.371	0.483
Lived in a city school district	0.142	0.349	0.128	0.334	0.224	0.417	0.183	0.387	0.793	0.405	0.710	0.454
Lived in a suburban school district	0.446	0.497	0.459	0.498	0.352	0.478	0.384	0.487	0.179	0.383	0.206	0.404
Lived in a town school district	0.146	0.353	0.151	0.358	0.158	0.365	0.177	0.382	0.011	0.106	0.045	0.207
Lived in a rural school district	0.267	0.442	0.262	0.440	0.266	0.442	0.255	0.436	0.016	0.126	0.039	0.193

Note. OGT = Ohio Graduation Test; OAA = Ohio Achievement Assessments.
[a]Baseline is defined as achievement on eighth-grade OAA math and reading.
[b]Prior math and reading OAA scores defined as students' achievement on OAA exams in the prior year.

Table 3
Ohio Traditional Public School and E-School Student Demographics Weighted by Charter Enrollment

	Traditional Public School Students (Weighted by Charter Enrollment)				Traditional Public School Students (Weighted by E-School Enrollment)				E-School Students (Weighted by Charter School Enrollment)			
	Elementary and Middle School		High School		Elementary and Middle School		High School		Elementary and Middle School		High School	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
High school achievement												
10th-grade math OGT (*z* score)			–0.565	1.020			–0.375	1.060			–0.746	0.924
10th-grade reading OGT (*z* score)			–0.540	1.100			–0.365	1.090			–0.411	1.030
10th-grade science OGT (*z* score)			–0.496	0.862			–0.331	0.900			–0.507	0.815
10th-grade writing OGT (*z* score)			–0.502	1.030			–0.380	1.040			–0.693	0.996
10th-grade social studies OGT (*z* score)			–0.440	0.894			–0.287	0.921			–0.498	0.879
Pass 10th-grade math OGT			0.718	0.450			0.774	0.418			0.675	0.468
Pass 10th-grade reading OGT			0.773	0.419			0.821	0.383			0.820	0.384
Pass 10th-grade science OGT			0.589	0.492			0.667	0.471			0.593	0.491
Pass 10th-grade social studies OGT			0.795	0.404			0.824	0.381			0.756	0.430
Pass 10th-grade writing OGT			0.690	0.463			0.749	0.434			0.670	0.470
Pass all five 10th-grade OGTs			0.498	0.500			0.580	0.494			0.460	0.498
Baseline math OAA (*z* score)[a]			–0.374	0.759			–0.204	0.816			–0.443	0.677
Baseline reading OAA (*z* score)[a]			–0.275	0.777			–0.142	0.798			–0.187	0.805
Elementary and middle school achievement												
Math OAA (*z* score)	0.004	0.993			0.015	0.988			–0.553	0.934		
Reading OAA (*z* score)	0.000	0.993			0.012	0.988			–0.248	1.010		
Prior math OAA (*z* score)[b]	–0.550	1.010			–0.307	1.040			–0.689	0.916		
Prior reading OAA (*z* score)[b]	–0.520	1.080			–0.296	1.070			–0.466	1.010		
Student demographics												
English language learner	0.025	0.156	0.054	0.226	0.025	0.156	0.043	0.203	0.001	0.0269	0.009	0.096
Gifted education	0.232	0.422	0.227	0.419	0.230	0.421	0.239	0.426	0.006	0.0769	0.100	0.300
Free and reduced price lunch program	0.453	0.498	0.787	0.410	0.445	0.497	0.656	0.475	0.588	0.492	0.780	0.414
Special education	0.151	0.358	0.164	0.370	0.150	0.357	0.149	0.357	0.153	0.36	0.200	0.400
Male	0.513	0.5	0.465	0.499	0.513	0.5	0.479	0.500	0.514	0.5	0.368	0.482
Number of disciplinary actions	0.245	1.15	0.544	1.560	0.240	1.140	0.524	1.640	0.020	0.264	0.390	1.610
Repeated grade	0.004	0.063	0.006	0.080	0.004	0.0628	0.006	0.074	0.029	0.167	0.006	0.075
Black student	0.158	0.365	0.602	0.490	0.146	0.353	0.435	0.496	0.116	0.321	0.285	0.451
Hispanic student	0.037	0.189	0.076	0.265	0.036	0.187	0.061	0.240	0.029	0.168	0.066	0.249
White student	0.746	0.435	0.275	0.447	0.758	0.428	0.451	0.498	0.799	0.401	0.598	0.490
Lived in a city school district	0.196	0.397	0.903	0.296	0.175	0.38	0.640	0.480	0.290	0.454	0.859	0.348
Lived in a suburban school district	0.410	0.492	0.080	0.272	0.421	0.494	0.251	0.434	0.319	0.466	0.101	0.302
Lived in a town school district	0.145	0.352	0.009	0.093	0.149	0.356	0.051	0.220	0.153	0.36	0.021	0.144
Lived in a rural school district	0.249	0.433	0.008	0.090	0.255	0.436	0.058	0.234	0.238	0.426	0.019	0.135

Note. OGT = Ohio Graduation Test; OAA = Ohio Achievement Assessments.
[a]Baseline is defined as achievement on eighth-grade OAA math and reading.
[b]Prior math and reading OAA scores defined as students' achievement on OAA exams in the prior year.

that the same students receive much lower test scores conditional on the control variables in Model 2. Furthermore, e-school students in the bottom two-thirds of the achievement distribution are significantly less likely to pass the 10th-grade OGTs than their peers in traditional public schools.

Discussion

Online schools in the K–12 education system have recently come under increased scrutiny and will likely be more controversial over the next several years. For example, e-school providers in Ohio have come under fire as their enrollments and revenue

Table 4
Linear Probability Model Predicting Enrollment in E-School Versus Charter School for Ohio's Elementary/ Middle and High School Students

	Elementary and Middle School			High School		
	(1)	(2)	(3)	(4)	(5)	(6)
Prior math OAA (*z* score)	–0.037***	–0.056***	–0.056***	–0.033***	–0.034***	–0.033***
	(0.003)	(0.005)	(0.005)	(0.009)	(0.009)	(0.008)
Prior reading OAA (*z* score)	0.024***	0.026***	0.026***	0.004	0.004	0.003
	(0.003)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)
Black student	–0.187***	–0.079	–0.178***	–0.244***	–0.148	–0.244***
	(0.035)	(0.076)	(0.035)	(0.030)	(0.116)	(0.031)
Hispanic student	–0.128***	–0.121***	0.004	–0.090***	–0.091***	–0.012
	(0.026)	(0.027)	(0.044)	(0.025)	(0.025)	(0.054)
Asian student	–0.03	–0.026	–0.026	–0.166*	–0.167*	–0.166*
	(0.034)	(0.029)	(0.030)	(0.076)	(0.076)	(0.076)
FRPL student	–0.021*	–0.025**	–0.025**	0.052***	0.052***	0.052***
	(0.010)	(0.009)	(0.009)	(0.016)	(0.016)	(0.016)
Special education student	–0.076***	–0.083***	–0.083***	–0.122***	–0.122***	–0.122***
	(0.020)	(0.019)	(0.019)	(0.029)	(0.029)	(0.029)
Gifted student	–0.046	–0.062*	–0.061*	0.094***	0.094***	0.094***
	(0.028)	(0.029)	(0.030)	(0.028)	(0.028)	(0.028)
LEP student	–0.106***	–0.096***	–0.095***	–0.023	–0.023	–0.025
	(0.023)	(0.017)	(0.017)	(0.052)	(0.052)	(0.052)
Retained in eighth grade	0.023	0.036+	0.037+	–0.003	–0.003	–0.003
	(0.020)	(0.019)	(0.019)	(0.048)	(0.048)	(0.048)
Value-added of eighth-grade school				–0.557**	–0.557**	–0.557**
				(0.175)	(0.174)	(0.175)
Black Student × City District		–0.089			–0.099	
		(0.073)			(0.121)	
Black Student × Suburban District		–0.136+			–0.104	
		(0.074)			(0.121)	
Black Student × Rural District		–0.217*			0.024	
		(0.100)			(0.140)	
Hispanic Student × City District			–0.135*			–0.078
			(0.055)			(0.063)
Hispanic Student × Suburban District			–0.124*			–0.069
			(0.050)			(0.069)
Hispanic Student × Rural District			0.021			–0.234*
			(0.060)			(0.097)
Constant	0.364***	0.328***	0.329***	0.142+	0.143+	0.142+
	(0.026)	(0.025)	(0.026)	(0.077)	(0.077)	(0.077)
R^2	0.068	0.075	0.074	0.103	0.103	0.104
N student/years	66,669	81,280	81,280	13,238	13,238	13,238
N districts of residence	603	601	601	510	510	510

Note. Models include students' prior district of residence fixed effects, and standards errors are in parentheses and clustered at the school level. OAA = Ohio Achievement Assessments; FRPL = free and reduced price lunch status; LEP = limited English proficient.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

have increased while the state has begun to question whether students are actually "attending" and learning in these school environments (Siegel, Candisky, & Bush, 2016). Thus, our findings make several contributions to the emerging debate and research surrounding online schooling in K–12 education (Ahn, 2016; CREDO, 2015). We show that there are stark patterns in which families and students are opting into e-schools compared to charter schools and those remaining in their local districts. The overall picture appears to be that students who are opting into the charter school sector are more likely to have lower prior academic achievement and come from lower socioeconomic status (SES) backgrounds. However, even within this group of students, and conditioning on students' prior achievement, poverty status, and residential district of record, we find stark differences

Table 5
Relative Difference in Probability of Enrolling in an E-School, Between Ohio's Minority Versus White Students, Within District Urbanicity

	Elementary and Middle Schools	High Schools
	(1)	(2)
Panel A: Difference between White and Black students attending e-schools		
Town district	–0.079	–0.148
	(0.076)	(0.116)
City district	–0.168***	–0.247***
	(0.035)	(0.038)
Suburban district	–0.215***	–0.252***
	(0.028)	(0.035)
Rural district	–0.296***	–0.125
	(0.066)	(0.079)
Panel B: Difference between White and Hispanic students attending e-schools		
Town District	0.004	–0.012
	(0.044)	(0.054)
City District	–0.131***	–0.089**
	(0.034)	(0.032)
Suburban District	–0.120***	–0.081⁺
	(0.024)	(0.042)
Rural District	0.025	–0.246**
	(0.045)	(0.080)

Note. Each cell contains the percentage point difference between White and Black/Hispanic students attending an e-school in a given geographic area. These are estimated from linear combinations of the coefficients from race and geographic indicators predicting e-school enrollment in Table 4. Clustered standard errors are in parentheses.
⁺$p < .10$. **$p < .01$. ***$p < .001$.

Table 6
Ohio Student Achievement in E-Schools and Charter Schools Relative to Students in Traditional Public Schools

	Panel A: Elementary and Middle School OAA Achievement	
	Math	Reading
E-school	–0.368***	–0.186***
	(0.008)	(0.013)
Charter school	0.044***	0.038***
	(0.009)	(0.008)
R^2	0.642	0.573
N student/years	1,376,794	1,378,629
N schools	2,925	2,926
p value e-school = charter school	.000	.000

	Panel B: 10th-Grade OGT Achievement				
	Math	Reading	Science	Social Studies	Writing
E-school	–0.230***	–0.128***	–0.179***	–0.284***	–0.356***
	(0.015)	(0.019)	(0.016)	(0.020)	(0.016)
Charter school	0.003	–0.045⁺	0.051*	–0.057*	–0.130***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)
R^2	0.648	0.529	0.56	0.51	0.476
N student/years	186,800	187,522	187,284	187,201	187,357
N schools	1,160	1,164	1,170	1,162	1,164
p value e-school = charter school	.000	.005	.000	.000	.000

Note. Models include students' eight-grade school fixed effects, and standard errors are in parentheses and clustered at the school level. OGT = Ohio Graduation Test; OAA = Ohio Achievement Assessments.
⁺$p < .10$. *$p < .05$. ***$p < .001$.

Table 7
Likelihood of E-School and Charter School Students Passing Ohio Graduation Tests on Their First Attempt Relative to Traditional Public School Students

	Math	Reading	Science	Social Studies	Writing	All Subjects
E-school	−0.083***	−0.030***	−0.096***	−0.120***	−0.080***	−0.144***
	(0.007)	(0.007)	(0.010)	(0.011)	(0.007)	(0.010)
Charter school	−0.015	−0.014	−0.007	−0.030*	−0.028*	−0.027+
	(0.012)	(0.011)	(0.016)	(0.015)	(0.013)	(0.016)
R^2	0.28	0.246	0.274	0.247	0.248	0.335
N student/years	186,800	187,522	187,284	187,201	187,357	186,402
N schools	1,160	1,164	1,170	1,162	1,164	1,160
p value e-school = charter school	.000	.201	.000	.000	.000	.000

Note. Models include students' eight-grade school fixed effects, and standard errors are in parentheses and clustered at the school level. OGT = Ohio Graduation Test; OAA = Ohio Achievement Assessments.
+ $p < .10$. *$p < .05$. ***$p < .001$.

Table 8
Marginal Effects of E-Schools and Charter Schools on Ohio Students Achievement by Students' Prior Achievement Tertiles

	Elementary and Middle School		High School				
	Math	Reading	Math	Reading	Science	Social Studies	Writing
E-school							
First tertile (low achievers)	−0.405***	−0.255***	−0.142***	−0.057**	−0.130***	−0.201***	−0.150***
	(0.027)	(0.026)	(0.014)	(0.019)	(0.016)	(0.020)	(0.012)
Second tertile	−0.360***	−0.144***	−0.233***	−0.099***	−0.188***	−0.271***	−0.336***
	(0.010)	(0.008)	(0.029)	(0.020)	(0.027)	(0.027)	(0.024)
Third tertile (high achievers)	−0.302***	−0.103***	−0.105*	−0.092***	−0.081*	−0.205***	−0.331***
	(0.040)	(0.013)	(0.049)	(0.023)	(0.033)	(0.029)	(0.046)
Charter school							
First tertile (low achievers)	0.048***	0.030***	0.003	−0.063*	0.048+	−0.062*	−0.120***
	(0.011)	(0.010)	(0.026)	(0.028)	(0.028)	(0.027)	(0.033)
Second tertile	0.033**	0.04***	−0.004	−0.019	0.044	−0.074	−0.160
	(0.011)	(0.008)	(0.032)	(0.034)	(0.036)	(0.033)	(0.034)
Third tertile (high achievers)	0.038*	0.059***	0.018	0.002	0.100*	0.007	−0.107*
	(0.015)	(0.012)	(0.039)	(0.050)	(0.042)	(0.041)	(0.043)

Note. Coefficients represent the marginal effect of a given tertile of prior achievement and school type on students' achievement. For example, each cell represents the achievement differences between an e-school or charter student in a given teritile of the prior achievement distribution and a student in the same tertile in a traditional public school. Models includes students' prior school fixed effects and the same controls as Table 6. Standard errors are in parentheses and clustered at the school level.
+$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

by race in terms of who enrolls in e-schools versus charter schools. In urban and suburban districts, White students are more likely to opt into e-schools while their minority peers are more likely to attend charter schools.

Our findings suggest the need for future research to develop nuanced descriptions of the context of online schooling. These details of context—the policy setting, school types, choices of students, and so on—are important because they will drive better questions for analysis. For example, we find stark racial and academic differences in families who choose e-schools in Ohio versus those who remain in their local districts or attend charter schools. Why are certain families choosing e-schools? Are there are cultural and social reasons for the choice patterns we observe? Perhaps minority, low SES families in urban and suburban areas are constrained in their choices and opt out of e-schools. These are deeper questions that can better inform more targeted policies to utilize online schools effectively in K–12 systems.

Our findings also suggest that students in e-schools may not be learning at the same rate as their peers in traditional public schools and charter schools, mirroring findings from a growing research base (Ahn, 2016; CREDO, 2015). We build on previous studies by examining achievement trends by students' prior achievement and find that while higher achieving students do better in e-schools than their lower achieving e-school peers, in most cases, they do not

Table 9
Marginal Effects of E-Schools and Charter Schools on Ohio Students Likelihood of Passing Ohio Graduation Tests on Their First Attempt by Students' Prior Achievement Tertiles

	Math	Reading	Science	Social Studies	Writing	All
E-school						
First tertile (low achievers)	–0.142***	–0.057**	–0.130***	–0.201***	–0.150***	–0.189***
	(0.014)	(0.019)	(0.016)	(0.020)	(0.012)	(0.012)
Second tertile	–0.034***	–0.008	–0.076***	–0.080***	–0.042***	–0.157***
	(0.010)	(0.006)	(0.012)	(0.012)	(0.010)	(0.017)
Third tertile (high achievers)	0.018	–0.001	–0.007	–0.006	0.012+	–0.021+
	(0.012)	(0.012)	(0.018)	(0.011)	(0.007)	(0.011)
Charter school						
First tertile (low achievers)	–0.031+	–0.042**	–0.016	–0.062**	–0.056**	–0.042*
	(0.016)	(0.015)	(0.020)	(0.019)	(0.018)	(0.019)
Second tertile	0.023+	0.026*	0.015	0.004	0.001	–0.034
	(0.014)	(0.012)	(0.018)	(0.015)	(0.013)	(0.023)
Third tertile (high achievers)	0.032*	0.042**	0.045**	0.047***	0.040**	0.066***
	(0.013)	(0.014)	(0.017)	(0.014)	(0.014)	(0.020)

Note. Coefficients represent the marginal effect of a given tertile of prior achievement and school type on students' likelihood of passing the OGT. For example, each cell represents the percentage point difference in the likelihood of passing the OGT between an e-school or charter student in a given teritile of the prior achievement distribution and a student in the same tertile in a traditional public school. Model includes students' prior school fixed-effects and the same controls as 6. Standard errors are in parentheses and clustered at the school-level.
+$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

perform as well as they would have in traditional public schools. Some high-performing high school students in e-schools, however, are passing the OGT assessments at the same rate as their traditional public school peers, which is a requirement for high school graduation.

These findings illuminate the importance of understanding the contexts of practice that occur in online school settings (Ahn, 2011). For example, it may be likely that asking students to independently work through curriculum online imposes heightened stresses on students such as the need to self-regulate learning and have advanced metacognitive skills in order to monitor and manage one's own learning process. These skills have been shown to be quite difficult to foster for learners and often require careful scaffolding and guidance (Azevedo, 2005). These stresses may be exacerbated for students who have lower prior academic achievement or are novices in a topic domain.

Understanding these details of context and pedagogy have substantial implications for how one interprets the outcomes of K–12 online schooling and the policy implications we derive. One potential but simplistic interpretation is that online schools are unequivocally negative for K–12 learners and policy should deter these school forms. A more nuanced understanding is that online schools—in its current form as a largely independent learning experience—are not effective for K–12 learners. Instead, learners still need the presence of teachers, mentors, or peers to help them through the learning process. This interpretation instead suggests different policy implications. States will need to pay more attention to how school choice policies influence the supply and provision of online schools to encourage certain student populations to enroll. In addition, online curriculum might be designed and employed to efficiently deliver content but combined with new ways of distributing human support (e.g., different teaching or mentoring practices) that could serve students more effectively. There is a critical need for future research that examines whether online schooling has differential effects on specific subpopulations and under what conditions.

In the history of educational technology research, it is well established that technology as a delivery mechanism (e.g., whether something is online or face-to-face) has no direct impact on student learning outcomes (Bernard et al., 2004; Clark, 1983; Fishman et al., 2013). What really matters is understanding how the introduction of technology impacts who chooses to participate in particular learning environments and what they experience that result in learning outcomes. As researchers strive to understand how online learning could be employed to improve student outcomes, there is a great need for research to contextualize findings and better articulate how online education is implemented in various ways, how policies shape what types of learners experience online learning, and importantly how online learning may likely have differential effects for students who have diverse academic needs and histories.

NOTES

[1]A parallel body of research evaluates the impact of online courses on students' outcomes. The main difference in this literature is that students are generally enrolled in traditional brick-and-mortar schools but supplement their education with online courses.

[2]In Ohio, e-schools are also considered and governed as charter schools. In this article, however, e-schools refer to schools that were approved to provide students with a fully (or at least majority) online education. Further, in this article, the term *traditional charter schools* will be used to indicate charter schools that are brick-and-mortar schools where students receive their education in a traditional face-to-face setting.

[3]As part of our data sharing agreement signed in 2013–2014, the research team and Ohio Department of Education decided on four years of data, equivalent to one full high school cohort.

[4]Students are required to score at least proficient in five Ohio Graduation Test (OGT) subjects. If they do not score at least proficient in 10th grade, they can repeat the exam in Grades 11 and 12 (see http://education.ohio.gov/Topics/Testing/Ohio-Graduation-Test-OGT for more information).

[5]It is also common for researchers to use logistic or probit regressions with binary dependent variables. The linear probability model (LPM) has two distinct advantages. First, the coefficients in a LPM are probabilities and therefore easier to interpret than coefficients from logistic or probit regressions. Relatedly, the LPM is easier to interpret when including fixed effects or interaction terms. Although there are potential limitations with LPMs, including predicted probabilities greater than one and mechanical heteroskedasticity, LPMs, logitistic, and probit regressions produce similar average marginal effects for continuous independent variables and similar discrete changes in predicted probabilities for binary independent variables (Angrist & Pischke, 2009; Wooldridge, 2010). For these reasons, we prefer the LPM to logistic and probit specifications.

[6]We could also estimate a multinomial logit model to include traditional public schools into the analysis. However, we are most interested in the direct comparison between students who pick an online charter versus a face-to-face charter school in the same geographic area.

[7]Here too we use $(t - p)$ to index variables that were measured p years prior to the current year. For models with elementary and middle school students, we measure prior achievement and schools fixed effects from the prior year (p = 1). For high school students, we fix students' achievement and district of residence fixed effects to their eighth-grade values (p = 2).

[8]Although not shown, we also used a doubly robust methodology that combines Equation 2 with inverse probability weights (IPW) (Imbens & Wooldridge, 2009). For this procedure, we first estimate the likelihood of attending a traditional public school, an e-school, or a charter school using a multinomial logistic regression. We used as our weight $\left(\frac{\hat{p}_s}{\hat{p}_e}\right)$, where $\hat{p}_s$ is the probability a student attended their actual school of record (e.g., the probability an e-school student attended an e-school), and $\hat{p}_e$ is the probability a student from any of the three schools attended an e-school. This weighting procedure weights the demographics of charter school and traditional public school students to match those of e-schools. We then estimate Model 2 using this weight (e.g., a weighted least squares regression model) and get qualitatively similar results. The results are available on request.

[9]Specifically, these coefficients represent the linear combination of the Black and Hispanic interactions from Columns 2, 3, 5, and 6 from Table 4.

[10]Although not shown, we also estimated models that controlled for the yearly charter market share within a residential district of record. The results of our racial comparisons did not change with the inclusion of this control variable. The results are available on request.

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Manuscript received March 10, 2015
Revisions received January 12, 2016,
August 16, 2016, and January 13, 2017
Accepted January 18, 2017